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Multiple Forecasting Techniques

OPERATIONS RESEARCH AND ECONOMIC ANALYSIS OFFICE

DEPARTMENT OF DEFENSE

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FOREWORD

Currently the Standard Automated Materiel Management System (SAMMS) uses a single technique to forecast demand for all hardware items. To evaluate, through implementation, the potential for improved forecasts using a variety of demand forecasting techniques, a Requirements Forecast Working Group (RFWG) was created by the Supply Management Division. The Defense Logistics Agency Operations Research and Economic Analysis Management Support Office (DORO), as a member of the RFWG, was tasked with an initial study of the methodology governing the use of a variety of forecasting techniques and the potential benefits of improved demand forecasts for DLA managed items.

The authors of this paper are indebted to RFWG participants who, through their comments, questions and ideas, have kept us on the right path which enabled the timely completion of this study.

We are also indebted to the Defense General Supply Center's Office of Planning Resource Management for their expertise in formulating the initial concepts into a study that could be successfully completed and implemented within current DLA policy.

Christine L. Gallo

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LIST OF ACRONYMS

SAMMS	Standard Automated Materiel Management System
RFWG	Requirements Forecast Working Group
QFD	Quarterly Forecast of Demand
MSE	Mean Squared Error
RMSE	Square root of the MSE
MAD	Mean Absolute Deviation
TAE	Total Absolute Error
MIPE	Modified Index of Predictive Efficiency
PERMES	Materiel Readiness System's Performance Projection Model

EXECUTIVE SUMMARY

The Defense Logistics Agency (DLA) currently employs the Standard Automated Materiel Management System (SAMMS) under a mode which forecasts demand for all Quarterly Forecast Demand (QFD) Items through the use of a single forecasting technique. This approach for these QFD items has been shown through previous analysis to result in long term forecasting errors. The result of these errors in forecasts is that DLA has consistently maintained higher safety levels which has contributed to the presence of excess on-hand stocks.

Consequently, the overall thrust of this analysis has been to enhance the forecasting methodology of SAMMS by exploring alternative forecasting techniques which would have the potential to enhance the accuracy of long term forecasts. These improvements could be accomplished through the development of an approach which would reduce the lead time forecasting errors inherent to the system. As important as these goals are today, they will be of greater concern in the near future as DLA's mission expands through the projected transfer of 1.4 million items currently maintained by the TRI-Services and is reflected by DLA's Strategic Plan under Materiel Management (i.e., Objective 3) which is to sustain customers in the most effective and efficient manner.

The project has succeeded in the development of a multiple forecasting methodology which has the capability to select the most appropriate forecasting technique for each QFD item. The study has found that a system improvement of 9 percent over the current SAMMS method could be achieved in forecasting accuracy. It was estimated that, while maintaining a constant supply availability rate, a $42 million non-recurring cost savings could be realized by implementation of this technique as an adjunct to SAMMS. These projected savings could substantially increase once the consumable item transfer of 1.4 million items for the TRI-Services is accomplished with implementation of this methodology supporting the Defense Management Review Decision (DMRD) #901 in the goal of reducing supply costs.

Specific recommendations stemming from this project are the following:

- Enhance the SAMMS forecasting methodology with a multiple forecasting model for QFD items as an adjunct to SAMMS.

- Implement the Multiple Forecasting Model at the Hardware Centers and for Medical. Use a staged process under the guidance of the Requirements Forecast Working Group (RFWG) chaired by the Supply Management Division. These stages will entail the following:

    - Develop a SAMMS linked prototype model.

    - Test the prototype model at a selected Hardware Center.

    - Extend the prototype model to all Hardware Centers and to Medical under full implementation.

I. INTRODUCTION

A. Background. Currently the Standard Automated Materiel Management System (SAMMS) uses a single technique to forecast demand for all hardware items. SAMMS forecasts are being adjusted by supply center with locally developed forecasting programs and manual inventory manager intervention. Previous DLA studies have focused on finding a single technique to improve forecasting for all items. A demand forecasting study of subsistence items has found that a set of four simple methods could perform better than the current subsistence techniques.

B. Purpose. The purpose of this study was to define the criteria for a multiple forecasting model to operate in conjunction with the current SAMMS system and data base. The multiple forecasting model optimally selects the most appropriate forecasting technique for each item.

C. Objectives. The objectives of this study are:

1. Identify appropriate forecasting techniques and evaluation methodology.

2. Define the data requirements for obtaining the best forecast for each item.

3. Provide recommendations for implementation strategies.

D. Scope of study.

1. Demand based replenishment items that are established and are currently forecasted on a quarterly basis were used.

2. Subsistence, fuels, clothing and textile items were not included.

3. Forecasting techniques studied were limited by their ability to forecast with a maximum of 20 quarterly data points allowing a minimum of the latest 4 quarters for forecast evaluation.

4. Items included in this study had 24 quarters of demand history, where zero demand is an acceptable history.

II. LITERATURE OVERVIEW

Research on potential forecasting techniques for use in a multiple forecasting system has focused on the ability to initialize and forecast with as little as 12 quarters of demand data.

It was not the intent of this study to evaluate each forecasting technique on the basis of previous empirical testing since testing can be conducted to favor one technique over others. A key assumption is that some methods are better, depending upon the characteristics of the time series used for forecast evaluation (2 p66).

Several key concepts were kept in the forefront of this project as research was conducted and various statistical measures and formulas were evaluated. First, simple techniques are at least as accurate as complex forecasting methods (15 p154,16 p142). Second, even the best statistical method explains only a small portion of the information contained within the demand stream (2 p61).

Two areas of consideration with demand data preparation are to check for outliers and deseasonalize the demand stream. Although there are varying methods to identify and adjust for outliers (11), the simplest, and possibly most effective method given large variances in demand, is to put upper and lower limits on acceptable demands (3). For example if a quarters demand is outside the acceptable bounds, set that period's demand equal to the limit. This approach will be referred to as demand dampening and is discussed in greater detail in section IX.C.

Deseasonalizing the data has not been shown to increase forecast accuracy (20,1 p173). Also since this study includes techniques designed to forecast demand data with seasonal characteristics, this type of data preparation was not necessary.

The combination of competing forecasting techniques is receiving a great amount of attention in current literature. Most agree that a better forecast can be obtained by combining the individual forecasts of two or more techniques. This may be more appropriate when the forecasting horizon is longer (3 p184). To combine forecasts, methods for computing the weight of each forecast are varied. An appropriate technique, which again is the simplest, is to use the arithmetic mean of the individual forecasts (2 p58,15 p155,16 p139). This was the approach undertaken for this study.

III. MULTIPLE FORECASTING

A. Assumptions. The concept of a multiple forecasting model centers on the following two assumptions which are based on work introduced by Smith (24).

1. One forecasting technique will be the best for a given item.

2. The technique that worked best in the past will work best in the future.

B. Description. A forecasting model was designed from these rather simple ideas. Consider an item with 20 quarters of demand history. The demand stream is broken into three parts. The first 12 quarters are defined as the **initialization period**. The initialization period is used to establish any constants or parameters associated with a forecasting technique. Regression and smoothing techniques use all demand points in the initialization period. Naive techniques, such as the last demand, use only one demand point.

The second part is the **testing period.** This represents the demand that is forecast using each of the available forecasting techniques. Forecasting error and bias are measured for each technique. Finally, from the criteria established by this study, one forecasting technique is selected to forecast an item's future demand.

The last 4 quarters are the **results period.** Only the selected technique was used to forecast demand for this time period. Forecasting accuracy of the model's selected technique was compared to the accuracy of a SAMMS forecast. The length of the results period, which was defined through discussion within the RFWG, is 1 year. The basis for this decision is in the length of item lead times and procurement cycles. One year roughly represents the average lead time plus 1 quarter (see Table 1 in Section VII).

To obtain an annual forecast for the results period, the QFD from the selected technique was modified in the following ways:

1. QFD * 4. This method is similar to the SAMMS' lead time demand computation.

2. QFD * 4 + short term trend. The short term trend is computed by the average testing period error.

3. QFD + long term trend. The long term trend is based on the slope of a regression line through the initialization and testing period demands.

4. Forecast from a forecast. This involves using the QFD as a bridge, or the next demand point, to obtain the next QFD. Four QFDs computed in this manner would then be used as the annual forecast.

In summary, the forecasting model reads the initialization and testing period demands. Any alteration of the actual demand, such as percent applicable nonrecurring demand, occurs at this point. Each of the available forecasting techniques are used to forecast demand over the testing period. Forecasting error and bias are measured. The criteria established by this study will then be used to select one forecasting technique to forecast future item demand. Forecasting accuracy of the selected technique will be compared to a SAMMS forecast.

IV. TESTING PERIOD

As previously mentioned, many events take place during the testing period. Forecasts are made, error and bias are measured, and one technique is selected. In this section various methods for measuring forecast error, applying the forecast to the testing period, and evaluating forecast bias are explored.

A. Forecast Accuracy Measures. Three testing period error measures were used to assess the accuracy of each forecasting technique. The Mean Absolute Deviation (MAD) is an average of absolute forecasting errors and the Mean Squared Error (MSE) is the average of squared forecasting errors. The MSE, by squaring the error, unproportionally places more emphasis on larger errors. This means that techniques yielding smaller MSEs decrease the potential for large forecasting errors. Total Absolute Error (TAE) is the difference between the sum of the forecasts and the sum of the demands. The TAE has an expected value of zero and could be interpreted as how well the future average demand is represented by the average forecast of demand. Error measures are defined as follows:

$$MAD = \frac{\sum_{t=1}^{n} ABS(A_t - F_t)}{n}$$

$$MSE = \frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}$$

$$TAE = ABS \sum_{t=1}^{n} (A_t - F_t)$$

where: F_t = forecast for time t

A_t = actual demand for time t

n = number of time periods

B. Applying the Forecast. Besides error measures, the application of the forecast to the testing period takes three forms. A forecast that is **straight-lined** has all subsequent values over the forecasting horizon equal to the current QFD. A forecast of this type potentially discriminates against seasonal forecasting techniques. **One-step ahead** forecasts are computed for only one period into the future. A combination of the these two types of forecast is called a **long-term** forecast. This is actually a series of long-term forecasts made with a leading time frame of one period.

C. Bias Measures. Detection of a forecast's bias incorporates the use of Theill's bias proportion. Using this statistic, which has an expected value of zero, a threshold limit must be established to eliminate potentially biased techniques. The proportion is defined as follows:

$$U = \left[\frac{\bar{A} - \bar{F}}{RMSE} \right]^2$$

where: $\bar{F}$ = average forecast

$\bar{A}$ = average actual demand

RMSE = square root of the MSE

D. Technique Selection. At least three decisions must be made before a forecasting technique can be selected as the "best" technique for a given item's demand. First, should biased techniques be eliminated from consideration? If so, what detection threshold will be used to establish a biased technique? Secondly, which of the identified accuracy measures will be minimized? And finally, which method for applying the forecast to the testing period will be used? The answers to these fundamental questions are developed in section IX.A. However, the basic premise behind the technique selection process is as follows:

1. Techniques that yield a bias value beyond the established threshold are eliminated.

2. The technique producing the least error is selected.

V. FORECASTING TECHNIQUES

The techniques studied for inclusion in the multiple forecasting model fall into 6 classes. All are time-series forecasting models which means that the forecast is based on historical demand. No assumptions are made with regards to the applicability of any technique to an individual demand stream. This is particularly important for the regression models and the standard assumptions that traditionally accompany them. A technique's forecast is viewed as simply a prediction, accurate or not, and the bias and accuracy of that prediction are subsequently evaluated.

The following definitions apply throughout the technique discussion:

F_t = Forecast for time period t

X_t = Actual demand for time period t

A. Naive methods. The following naive forecasts are easily computed however these methods would overreact to one-time surges or outliers in the demand stream.

1. The basic naive forecast assumes that the next period's demand is the same as this period's. The forecast is generated as follows:

$$F_{t+1} = X_t$$

2. The seasonal naive forecast assumes that the next period's demand is the same as the demand 1 year ago. The forecast for quarterly demand with a season length of 4 quarters is generated as follows:

$$F_{t+1} = X_{t-3}$$

B. Moving averages.

1. A simple moving average forecast is an average of the most recent demands. The number of periods to include in this average is generally a multiple of the season length and therefore is free of seasonal effects. The 4 and 8 quarter moving average forecasts are respectively given by:

$$F_{t+1} = \sum_{t-3}^{t} X_i \quad /4$$

$$F_{t+1} = \sum_{t-7}^{t} X_i \quad /8$$

2. A lagged 2 quarter moving average that is based on autocorrelation analysis was also used. This analysis determines if there is a relationship between quarters at two, three, or four intervals apart. Autocorrelations are computed for the first four lags and a 95 percent confidence interval is used to establish significance. This method will employ the following decision rules:

(a) If the second autocorrelation is positively significant then:

$$F_{t+1} = (X_{t-1} + X_{t-3})/2$$

(b) If the third autocorrelation is positively significant then:

$$F_{t+1} = (X_{t-2} + X_{t-5})/2$$

(c) If the fourth autocorrelation is positively significant then:

$$F_{t+1} = (X_{t-3} + X_{t-7})/2$$

(d) If none of the above are true then:

$$F_{t+1} = (X_t + X_{t-1})/2$$

C. Exponential smoothing. There are many exponential smoothing models documented. Each method may attempt to compensate for changes in the demand stream such as trend, seasonality, or level. With possibly the exception of Winter's method, the class of exponential smoothing models is noted for minimal data requirements and low cost for computer time thus making them popular for large inventory systems. Initial smoothing values for these models were generated by using an average of the first 4 quarters of the time series and by using the y-intercept value of a regression line through the time series. In addition, for each of these techniques various smoothing parameters were tested. Smoothing parameters were generally chosen between 0.05 and 0.3. The higher the parameter the more weight that is given to the current observation or value.

1. Single exponential smoothing is a weighted average of the previous forecast and the most recent demand. The forecasting model takes the form:

$$F_{t+1} = \alpha X_t + (1 - \alpha) F_t$$

2. Brown's double exponential smoothing uses a smoothing equation to smooth the current demand and a second to smooth the smoothed value of the first equation. This technique provides a trend estimate; however, it is not currently used in SAMMS. The SAMMS modification is to drop the last term, "b" from the forecast equation below. A forecast is generated from the following:

$$S'_t = \alpha X_t + (1 - \alpha) S'_{t-1}$$

$$S''_t = \alpha S'_t + (1 - \alpha) S''_{t-1}$$

$$a_t = 2S'_t - S''_t$$

$$b_t = [\alpha/(1 - \alpha)](S'_t - S''_t)$$

$$F_{t+m} = a_t + b_t m$$

where: S' = single smoothed quantity
S'' = double smoothed quantity
α = smoothing parameter
m = length of forecasting horizon

3. Hclt's double exponential smoothing is similar in principle to Brown's except that it smooths the trend values separately and with an additional smoothing parameter. The forecast is given by the following set of equations:

$$S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + b_{t-1})$$

$$b_t = \delta(S_t - S_{t-1}) + (1 - \delta)b_{t-1}$$

$$F_{t+m} = S_t + b_t m$$

where: S = smoothed quantity
b = trend component
α = smoothing parameter
δ = smoothing parameter for trend
m = length of forecasting horizon

4. Winter's triple exponential smoothing is the only smoothing model to be studied that directly deals with seasonal data. The method is composed of three smoothing equations for the level, trend, and seasonality of the time series.

$$S_t = \alpha X_t/I_{t-L} + (1 - \alpha)(S_{t-1} + b_{t-1})$$

$$b_t = \delta(S_t - S_{t-1}) + (1 - \delta)b_{t-1}$$

$$I_t = \beta X_t/S_t + (1-\beta)I_{t-L}$$

$$F_{t+m} = (S_t + b_t m)I_{t-L+m}$$

where: S = smoothed quantity
b = trend component
I = seasonal component
α = smoothing parameter
δ = smoothing parameter for trend
β = smoothing parameter for seasonality
m = length of forecasting horizon

5. Trigg-Leach adaptive response rate exponential smoothing models were designed to automatically adjust the smoothing parameter used in single exponential smoothing. Parameter adjustment is based on forecast error thus accommodating a sudden shift in the level of the series. In attempts to keep the smoothing parameter from overreacting to occasional demand spikes or outliers, alterations of the original Trigg-Leach model were made. The two modified methods studied use the following for parameter estimation:

$$e_t = X_t - F_t$$

$$E_t = \beta e_t + (1-\beta)E_{t-1}$$

$$M_t = \beta|e_t| + (1-\beta)M_{t-1}$$

$$\alpha_t = |E_t \;/\; M_t|$$

where: e = forecasting error
E = smoothed forecasting error
β = smoothing parameter for error
M = smoothed absolute error
α = computed smoothing parameter

(a) Delayed α Trigg-Leach model uses the α computed from a previous forecast for the current forecast.

$$F_{t+1} = \alpha_{t-1}X_t + (1 - \alpha_{t-1})F_t$$

(b) Smoothed α Trigg-Leach model smooths the computed α to dampen it's response(19 p7).

$$\alpha'_t = \delta(\alpha_t) + (1 - \delta)\alpha'_{t-1}$$

$$F_{t+1} = \alpha'_t X_t + (1 - \alpha'_t)F_t$$

D. Regression models.

1. The simple linear regression model applies ordinary least squares to fit a straight line through the available demand data. The assumption is that demand will remain relatively stable or increase or decrease in a linear fashion. The forecast is generated as follows:

$$b = \frac{n\Sigma XY - (\Sigma X)(\Sigma Y)}{n\Sigma X^2 - (\Sigma X)^2}$$

$$a = (\Sigma Y)/n - (b\Sigma X)/n$$

$$F_m = a + bm$$

where: Y = the period of the time series
n = the number of quarters included
m = length of forecasting horizon

2. The nonlinear regression model uses ordinary least squares to fit a straight line through the available log transformed demand data. In a strict definition this technique is linear in its parameters and is therefore a linear model. However to differentiate from the simple linear regression technique defined above, the word "nonlinear" is used. This technique applies an exponential curve to describe the time series. The forecast is generated as above by first taking the natural log of the demand data. After applying the computations the forecast is simply the antilog of the computed value.

E. Probability models. To accommodate a large number of zeros in a time series, a conditional probability method was studied. Each quarterly data point was transformed to "1" if the demand was greater than zero or a "0" if the demand equals zero. The basis for its use depends on "clustering" or in other words, a time series that has a greater tendency for a "0" demand following a "0" demand (similarly a "1" following a "1")(8). This method incorporates the following decision rules:

1. If $P(1)=0$ then $F = 0$.

2. If $P(0)=0$ then F = global mean of the demand series.

3. If $P(1|1) >= P(0|1)$ then F = average of the previous actual demand since the last zero demand.

4. If $P(1|0) > P(0|0)$ then F = average of the previous actual demand since the last zero demand.

5. If none of the above are true then $F=0$.

where: F = QFD

P(1) = probability that the transformed demand equals 1

P(0) = probability that the transformed demand equals 0

P(1|1) = probability that the transformed demand equals 1 given that the previous demand equals 1

P(0|1) = probability that the transformed demand equals 0 given that the previous demand equals 1

P(1|0) = probability that the transformed demand equals 1 given that the previous demand equals 0

P(0|0) = probability that the transformed demand equals 0 given that the previous demand equals 0

F. Combinations of models. An average of each pair of forecasting techniques was used as a forecast.

VI. EVALUATION MEASURES

The criteria used for evaluating the forecasting model's performance, or accuracy, was an area of particular concern for this study. The decision should come from the manager to insure agreement with DLA policies and goals (20,17 p4,12 p32). Management's view of what is most important with regard to forecast accuracy can then be translated into appropriate error computations. In contrast to the forecast accuracy measures that are used in the technique selection process and are computed over the testing period (section IV), the evaluation measures, described here, are computed from forecast error over the results period. In other words, after a technique is selected to forecast an item's demand, it will be evaluated by its ability to forecast the future. This is termed the forecasting model's evaluation and encompasses more than the selected technique's forecasting accuracy; but also, and more importantly, the process by which the model selects that technique.

The Modified Index of Predictive Efficiency (MIPE) is a relative measure that provides an item by item comparison of SAMMS forecast to the model forecast. It is computed as follows:

$$\text{MIPE} = 100 * \left[\frac{(E_S - E_m)}{\frac{1}{2}(E_S + E_m)} \right]$$

where: E_S = TAE of SAMMS' forecast

E_m = TAE of model's forecast

Although there are some obvious difficulties in interpreting the MIPE, it has two characteristics which make it a good choice at this time. First, the MIPE provides a comparison to the forecast generated by SAMMS on an item by item basis. Thus each item's forecasting accuracy has the same weight. This trait was desirable to prevent forecasts for a few high-demand items from having a large impact on the results. Second, it enabled a fair comparison between the accuracy of the model's forecast and that of SAMMS. To illustrate these robustful qualities, consider the following example.

1. Model's forecast error = 3
   SAMMS' forecast error = 1

   Percent error reduction = 100 * (1 - 3)/1 = -200%
   MIPE = 100*(1 - 3) / [½*(1 + 3)] = -100%

2. Model's forecast error = 1
   SAMMS' forecast error = 3

   Percent error reduction = 100 * (3 - 1)/3 = 67%
   MIPE = 100*(3 - 1) / [½*(3 + 1)] = 100%

As this example illustrates, SAMMS' forecasts are favored when computing a simple percent reduction. When the model's forecasting error was two units more than SAMMS', its performance was 200 percent less. However when the model's error was two units less, its performance was only 67 percent more. By using the MIPE both cases yield equal, but opposite, results.

Two additional evaluation measures were also used as forecasting accuracy measures and were discussed section IV.A. The MAD was used for selected analyses, such as long-term system performance (sections IX.D.2 and IX.E), because of its computational efficiency over the MIPE. The TAE is used throughout, but primarily as a raw value to complement relative measures.

VII. DEMAND BASE DEVELOPMENT

Items included for this study and their respective characteristics, such as procurement cycle period and lead times, were taken from the Supply Control Files in second quarter FY 1989. Demand histories were constructed by using the Supply Control Files from second quarter FY 1984 through second quarter FY 1989. The criteria for the selection of items included the following.

1. Demand supported replenishment items (Item Category Code "1")

2. Established items (Age of Item Code "E")

3. Stocked items (Supply Status Codes other than "2," "3," "9")

4. Quarterly forecasted items (Forecast Basis Code "2")

5. The item must have 6 years of available demand history where zero demand is an acceptable history.

The multiple forecasting model's evaluation focused on yearly forecast accuracy. The length of the forecast horizon requires consideration of the amount of time it takes to procure and stock an item. Given that a forecast is accurate for events over the next 30 or 90 days, the resources to react to that forecast may not be available. Table 1 represents some pertinent characteristics of the items selected according to the stated criteria.

TABLE 1
POPULATION ITEM CHARACTERISTICS

COMMODITY	NUMBER OF ITEMS	AVG PROCUREMENT CYCLE PERIOD (DAYS)	AVG TOTAL LEAD TIME (DAYS)
Construction	80,668	552	213
Electronics	130,184	744	231
General	75,664	746	213
Industrial	215,370	872	272
Medical	9,771	532	251

Three samples of items for each commodity were used for the analysis. Because of the larger population size and to provide roughly similar sample sizes for each commodity, the percent of Industrial items sampled is smaller. The following is a list of the samples and their respective purposes. The population percentage for Industrial samples is contained in parenthesis.

TABLE 2
ITEM SAMPLES

SAMPLE	POPULATION PERCENT	PURPOSE
1	2 (1)	Selection process analysis
2	2 (1)	Demand base analysis
3	10 (5)	Validation and summary statistics

VIII. SAMMS FORECAST

To evaluate the performance of the multiple forecasting model, comparisons were made to the accuracy of a SAMMS forecast. SAMMS forecast is a double exponential smoothing technique (see section V.C.2). Total demand, which consisted of recurring and nonrecurring demands, was used for the forecast generation. No efforts were made to exclude certain types of demands. Smoothing constants were initialized with a four quarter average and an alpha of 0.2 was used as the smoothing parameter. Comparisons were also made using a SAMMS' alpha of 0.15; however, limited sensitivity analysis reveals that the difference in total performance was insignificant.

The recorded QFDs were not used for the comparitive analysis. This was necessary since at times great disparity exists between the QFD of record and the demand history. This difference is not well understood and limited analysis suggests that this results from SAMMS single and double smoothed quantities that are either revised to accommodate competing supply objectives or are simply in error (31). This does not indicate that any alteration of these quantities has a negative impact on supply management goals; but, rather, that any comparative analysis conducted using recorded QFDs may introduce inadequacies that would prevent long-term predictability of forecasting requirements.

IX. ANALYSIS

A general form of the forecasting model was defined in Section III. The determination of the best combination of criteria that would govern the model's selection and forecasting process is a complex task because of the many alternatives previously presented. For this reason, detailed testing of the model's actual performance was delayed until its operation was more clearly defined. During the early stages of the project, emphasis was placed on the development of point estimates to include measures of the average error. Subsequently, these average performance measures were employed to expedite model development. Once defined, more rigorous performance testing could be conducted.

The first task, which is discussed in section IX.A, was to determine how the forecasting model would select the best forecasting technique for an item. Secondly, and with that selection process in place, which subset of forecasting techniques provides the best results. The identification of the subset of techniques is presented in section IX.B. Remaining areas of analysis, such as the most appropriate demand base and system impact issues, will follow.

A. SELECTION PROCESS. The selection process is the core of the multiple forecasting model. It defines how to select the "best" forecasting technique from all available forecasting techniques. This analysis comprised the evaluation of various types of forecast application, error measures and thresholds for bias detection. The following matrix depicts the various alternatives evaluated.

TABLE 3
SELECTION CRITERIA ANALYSIS MATRIX

ERROR:	MSE			MAD			TAE		
BIAS DETECTION:	.0	.2	.4	.0	.2	.4	.0	.2	.4
FORECAST APPLICATION One-step ahead			**EVALUATE**						
Straight-lined					**PERFORMANCE**				
Long Term							**MEASURES**		

As illustrated, there were 27 alternatives and, for each alternative, there were four methods of obtaining a yearly forecast from the selected technique (see Section III.B). By comparing the MIPEs, the top three alternatives, listed below, were identified for further study.

1. Commodity: General

   a. ALTERNATIVE 1:
   Minimize the MSE from one-step ahead forecasts.
   Detect bias at the 0.4 level.
   Obtain an annual forecast by multiplying the QFD by four.

   b. ALTERNATIVE 2:
   Minimize the MAD from one-step ahead forecasts.
   Detect bias at the 0.2 level.
   Obtain an annual forecast by summing four QFDs based on using previous forecasts as the actual demand.

   c. ALTERNATIVE 3:
   Minimize the TAE from one-step ahead forecasts.
   Detect bias at the 0.4 level.
   Obtain an annual forecast by multiplying the QFD by four.

2. Commodity: Industrial

   a. ALTERNATIVE 1:
      Minimize the MSE from one-step ahead forecasts.
      Detect bias at the 0.4 level.
      Obtain an annual forecast by multiplying the QFD by four.

   b. ALTERNATIVE 2:
      Minimize the MSE from one-step ahead forecasts.
      Detect bias at the 0.4 level.
      Obtain an annual forecast by summing four QFDs based on using previous forecasts as the actual demand.

   c. ALTERNATIVE 3:
      Minimize the TAE from one-step ahead forecasts.
      Detect bias at the 0.4 level.
      Obtain an annual forecast by multiplying the QFD by four.

Again, the three alternatives for each commodity presented here represent the best of the 27 total alternatives for each commodity that was evaluated. Although the actual scores, or MIPEs, for each alternative are not provided, some important observations will be noted by examining the top three cases. First, similarity exists with the identified alternatives for each commodity. Alternatives 1 and 3 for each commodity are the same. Second, the one-step-ahead forecast was consistently better than the other methods of forecast application. This was a criteria in each alternative for each commodity. Finally, higher bias detection thresholds were common for these alternatives.

Each alternative's performance may vary as different subsets of forecasting techniques are included. Therefore, each alternative was put through the technique elimination process.

B. TECHNIQUE ELIMINATION. Contained within the forecasting model were 171 forecasting techniques. This total included 18 single techniques and all possible two-way combinations of the single techniques. For forecasting each item's demand, the model chooses one of the 171 techniques based on the selection criteria.

The field of forecasting techniques needed to be narrowed. An observation made during the selection process analysis suggests that some of the techniques were selected as the best based on previous data but performed poorly when used to make new forecasts. In addition, the large number of techniques greatly increased the model's computer run time. Following, is a list of single techniques as described in Section V.

1. Four quarter moving average (MEAN4)
2. Eight quarter moving average (MEAN8)
3. Lagged moving average based on autocorrelations (ACORR)
4. Single exponential smoothing with alpha=0.1 (SES.1)
5. Single exponential smoothing, alpha=0.2 (SES.2)
6. Double exponential smoothing, alpha=0.1 (DES.1)
7. Double exponential smoothing, alpha=0.2 (DES.2)
8. SAMMS Double exponential smoothing, alpha=0.2 (DESnt)
9. Adaptive response single exponential smoothing (ARRS2)
10. Adaptive response single exponential smoothing with a smoothed alpha (ARRSA)
11. Holt's double exponential smoothing (HOLTS)
12. Winter's triple exponential smoothing, alpha=0.1 (WINT1)
13. Winter's triple exponential smoothing, alpha=0.2 (WINT2)
14. Conditional probability model based on clustering (CPROB)
15. Simple linear regression (REGRS)
16. Nonlinear regression (NLREG)
17. Last demand (LASTD)
18. Year ago demand (YRAGO)

For each run of the forecasting model a MIPE was computed to measure single forecasting technique performance. The MIPEs for the single techniques were then aggregated to produce an overall model performance. The single technique with the lowest MIPE was eliminated, one at a time, until the overall model MIPE showed no improvement. As this implies, the forecasting model was run approximately 15 times for each of the top three alternatives that were identified in section IX.A for each commodity.

This was not an exhaustive search for the right techniques for each selection alternative. However, it did provide a systematic means to review the performance of the forecasting techniques and provide a respectable set of techniques which ensured the completion of this study. A pertinent statement by McCullagh & Nelder is given (30 p23):

> "Even if we could define exactly what is meant by an optimum model in a given context, it is most unlikely that the data would indicate a clear winner among the large number of competing models. We must anticipate that, clustered around the 'best' model will be a set of alternatives almost as good and not statistically distinguishable."

This does not imply that the search for better techniques should abruptly end; but continuation at this point would involve a considerable amount of analysis with minimal additional payoff.

The amount of data already generated as a result of approximately 90 forecasting model applications (15 runs per 3 alternatives per 2 commodities) has become somewhat burdensome. Although this data is readily available, it will not be provided here for clarity and report size limitations. Listed below are the most appropriate subsets of the single forecasting techniques for each of the top three selection alternatives defined in Section IX.A.

1. Commodity: General

   a. ALTERNATIVE 1:
      MEAN4, MEAN8, SES.1, REGRS, NLREG

   b. ALTERNATIVE 2:
      MEAN4, MEAN8, ACORR, SES.1, DES.1, ARRSA, NLREG

   c. ALTERNATIVE 3:
      MEAN8, ACORR, SES.1, NLREG

2. Commodity: Industrial

   a. ALTERNATIVE 1:
      MEAN4, MEAN8, SES.1, NLREG

   b. ALTERNATIVE 2:
      MEAN4, MEAN8, YRAGO, SES.1, DES.1

   c. ALTERNATIVE 3:
      MEAN8, YRAGO, SES.1, NLREG

In addition to the sets of single techniques presented above, all possible two-way combinations within each set is implicitly included. Again, these sets of techniques were identified as appropriate techniques for each alternative. The alternatives now encompass not only the method, or criteria, used to select the best technique, but also, the set of techniques from which selections can be made.

An important similarity between each alternative for each commodity is that MEAN4, MEAN8, SES.1, and NLREG were typically included. So regardless of which selection alternative is employed, roughly the same subset of forecasting techniques constituted a better performer. A second observation is that within each subset is a varied group of techniques. The similarity among alternatives and the variety within each alternative lend some credibility to the technique elimination process employed for this study. Summary results for annual forecast accuracy are contained in Table 4.

TABLE 4
SELECTION ALTERNATIVE RESULTS
ITEM SAMPLE 3

GENERAL	ALTERNATIVE	AVERAGE MIPE(%)	AVERAGE TAE
	1	4	208
	2	4	219
	3	3	213
	SAMMS	N/A	219

INDUSTRIAL	ALTERNATIVE	AVERAGE MIPE(%)	AVERAGE TAE
	1	6	904
	2	3	943
	3	2	942
	SAMMS	N/A	957

The selection procedure defined for alternative one outperforms the others with higher predictive efficiencies, MIPEs of 4 and 6 percent, and lower absolute errors, TAEs of 208 and 904, respectively by commodity. Intuitively, one selection procedure will provide better results for each commodity. This idea is confirmed by the similar results obtained for the General and Industrial commodities.

Realizing that different supply centers manage items that contain different types of demand patterns, the technique elimination was continued. The technique elimination procedure for Construction yielded the same set of forecasting techniques as Industrial (MEAN4, MEAN8, SES.1, NLREG). Analysis of Medical item demands yielded a slightly different set of techniques than those listed above; however, when comparing the set of techniques selected for Medical to those selected for General, Industrial, and Construction no measurable difference in the model's performance was observed. Based on these results, the same set of techniques were applied to the Electronics commodity.

The set of appropriate techniques has not been examined in enough detail to say, "Yes, this is the **best** set of techniques for this commodity." However some conclusions can be drawn. Smoothing models perform better at lower alpha levels. Techniques should minimize the potential for volatile forecasts, thereby minimizing the loss should an inappropriate technique be selected. Some diversification must exist among the set of techniques. Seasonal techniques were not as effective and is most likely due to a yearly forecast horizon. Finally, continued improvements can be made by ongoing studies.

C. DEMAND BASE ANALYSIS

1. **Dampening.** Some DLA managed items have a tendency for extreme demands. Regardless of the magnitude, these can skew forecasts and make them almost meaningless. An attempt was made to smooth, or dampen, the demands. Dampening is defined as establishing upper and lower limits on acceptable demands. If a time period's demand is beyond the set limits, the demand is altered to be equal to the limit. Dampening would take place within the forecasting model and thus not artificially change the demand of record.

Establishing the limits is an extremely difficult task. Care must be taken to include real changes in the demand structure while eliminating the impact of outliers. Any criteria established is potentially biased and could result in serious departures from the expected value of demand. Limited analysis of these problems is continued in section IX.G. The limits evaluated were multiples of the standard deviation of demand such as 1, 2, or 3 standard deviations from the average item demand. This criteria could be applied evenly to all items. The following actual demand streams for two medical items will serve as examples for further discussion.

ITEM A:

QUARTER	1	2	3	4	5	6	7	8	9	10	11	12
ACTUAL	0	0	12	0	36	11	369	211	331	455	762	890
MODELS	0	0	12	0	36	11	**142**	**142**				

ITEM B:

QUARTER	1	2	3	4	5	6	7	8	9	10
ACTUAL	2364	2654	2415	39317	3456	3225	824	4108	5056	2326
MODELS	2364	2654	2415	**14537**	3456	3225				

Actual item quarterly demand is represented by the "ACTUAL" row. Item demand dampened to within one standard deviation of the mean, 142 for item A and 14,537 for item B, is represented by the "MODELS" row. The forecasting model's yearly forecast would be for the last four quarters of actual demand. Sixteen quarters of data were available for each item but only the most recent is sufficient for our discussion. For both items, the four quarter moving average was the selected technique.

Item A is an example of when not to dampen the demand stream and was reflected in a large forecast error. Dampening that occurred in quarters seven and eight prevented the forecasting model from detecting a trend. Item B is an example of the appropriate use of dampening. Dampening that occurred at quarter four reduced the model's forecasting error by 50 percent.

To compensate for both types of demand streams, a routine was developed to permit flexibility in the dampening process by attempting to identify a changing demand mean. In particular, the latest available data to be used in a forecast was not dampened if more than one quarter was beyond the established limit. Therefore for the first item, no dampening would take place. Various levels of dampening were examined and the results for yearly forecast errors are shown in Table 5.

TABLE 5
DEMAND DAMPENING
ITEM SAMPLE 2

GENERAL	DEGREE OF DAMPENING	AVERAGE MIPE(%)	AVERAGE TAF
	UNDAMPENED	0	165
	3 STANDARD DEVIATION	1	163
	2 STANDARD DEVIATION	4	158
	1 STANDARD DEVIATION	7	142
	SAMMS	N/A	166

INDUSTRIAL	DEGREE OF DAMPENING	AVERAGE MIPE(%)	AVERAGE TAE
	UNDAMPENED	5	1136
	3 STANDARD DEVIATION	6	1125
	2 STANDARD DEVIATION	8	1081
	1 STANDARD DEVIATION	11	1073
	SAMMS	N/A	1200

As depicted, the model's forecasting accuracy improved dramatically as the demand stream was dampened. Dampening not only improved the forecasts but also had a synergistic effect on the technique selection process. By reducing the noise the model could more appropriately select the best forecasting technique.

2. Recurring and nonrecurring demand. The second part of the demand base analysis was to determine the types of demands to use in the forecasts. There were two components of demand under consideration: recurring and nonrecurring. Initially the coefficient of variation was computed for all quarterly forecasted items. As shown in Appendix A, the demand variability was reduced by adding recurring and nonrecurring (total) demand quantities. Even when only one quarter, of twenty, experienced nonrecurring demand the associated variability was lower for total demand than recurring demand only.

TABLE 6
NONRECURRING DEMAND ANALYSIS
BY SELECTION ALTERNATIVE
ITEM SAMPLE 2

GENERAL	PERCENT OF NONRECURRING	AVERAGE MIPE(%)	AVERAGE TAE
	100	7	142
	50	11	140
	0	14	141
	SAMMS	N/A	166

INDUSTRIAL	PERCENT OF NONRECURRING	AVERAGE MIPE(%)	AVERAGE TAE
	100	11	1073
	50	12	1065
	0	10	1092
	SAMMS	N/A	1200

The annual forecast errors for various levels of nonrecurring demand are given in Table 6. Some differences were evident as a smaller percentage of nonrecurring demand was applied to the model's forecasts. However the differences for each commodity provided conflicting results. Moreover, there may be little consistency in labeling each demand as either recurring or nonrecurring. Since the dampening procedure is fairly applied to all items and still limits the effects of occasional demand spikes, total demand was used in the forecast generation process. The demand analysis of the remaining commodities suggests similar results and conclusions.

To summarize the demand analysis, below are the model's current parameters and performance results for annual forecast errors by commodity.

Current model parameters:

Minimize the MSE from one-step ahead forecasts.
Detect bias at the 0.4 level.
Obtain a annual forecast by multiplying the QFD by four.
Single techniques included: MEAN4, MEAN8, SES.1, NLREG
Technique combinations included: all possible 2-way combinations of the single techniques
One standard deviation demand dampening
Total demand: recurring and nonrecurring

TABLE 7
MULTIPLE FORECASTING MODEL SUMMARY RESULTS
ITEM SAMPLE 3

COMMODITY	MIPE (%)	AVERAGE TAE	SAMMS AVERAGE TAE	% TAE REDUCED
Construction	8	219	233	6
Electronics	8	129	144	10
General	10	196	219	11
Industrial	10	865	957	10
Medical	4	482	533	10

3. **TIMING ANALYSIS.** Timing analysis deals with the amount of data that is sufficient to obtain improved forecasts. More data may yield more accurate forecasts or may introduce extraneous information into the demand stream, slow the model's forecasting speed and create larger data files to be stored. Too little data may yield meaningless forecasts. In addition the data can be allocated to the initialization and testing periods in various ways. Table 8 displays the timing alternatives that were evaluated.

TABLE 8
TIMING ALTERNATIVE DEFINITIONS

ALTERNATIVE	1	2	3
INITIALIZATION LENGTH	12	8	8
TESTING LENGTH	4	4	8
QUARTERS OF DATA REQUIRED	16	12	16

Alternative one, a 12 quarter initialization and 4 quarter testing period, was used until the forecasting model was more clearly defined. The results for alternative one were previously displayed in Table 7 as summary results. The results for timing alternatives two and three follow respectively in Tables 9 and 10.

TABLE 9
TIMING ALTERNATIVE 2 RESULTS
ITEM SAMPLE 3

COMMODITY	MIPE (%)	AVERAGE TAE	SAMMS AVERAGE TAE	% TAE REDUCED
Construction	6	227	233	3
Electronics	7	132	144	8
General	9	205	219	6
Industrial	8	873	957	9
Medical	4	473	533	11

TABLE 10
TIMING ALTERNATIVE 3 RESULTS
ITEM SAMPLE 3

COMMODITY	MIPE (%)	AVERAGE TAE	SAMMS AVERAGE TAE	% TAE REDUCED
Construction	9	223	233	4
Electronics	7	139	144	3
General	9	195	219	11
Industrial	9	885	957	8
Medical	2	527	533	1

Alternative one, a 12 quarter initialization and four quarter testing period, yielded more accurate forecasts. This conclusion may be the result of bias inherent within this analysis since this alternative was used to establish the testing period parameters. However, the following observations were made. First, consistency in forecasting accuracy across commodities is greater with the first alternative. Secondly, the eight quarter testing period used for alternative three may not be responsive to the most recent demand changes. Finally, alternative two, since it requires fewer data points, may be applied to items with shorter demand histories.

D. OTHER STATISTICS AND PERFORMANCE RESULTS

1. Lead time error. The evaluation of the forecasting model's performance had been based on a yearly forecasting horizon. A year was chosen as the average lead time, approximately three quarters, plus one quarter. However there exists a wide range of lead times for DIA items. The lead time forecasting errors show similar increases in accuracy with the multiple forecasting model and are depicted in Table 11.

TABLE 11
LEAD TIME FORECASTING ERROR
ITEM SAMPLE 3

COMMODITY	MIPE (%)	AVERAGE TAE	SAMMS AVERAGE TAE	% TAE REDUCED
Construction	7	173	187	7
Electronics	9	111	126	12
General	10	153	173	12
Industrial	11	789	882	11
Medical	6	316	348	9

2. Dynamic vs. Static. Two methods of model implementation were analyzed. A dynamic forecasting model allows an item's assigned forecasting technique to change for each quarterly forecast. The forecasting model would evaluate each forecasting technique for each item every quarter. Concerns regarding this mode of operation include potential problems with respect to computer run time and a negative effect from the churning or changing of forecasting techniques possibly every quarter.

The second method of implementation is based on a static forecasting model. This model would select the best technique for an item for the first quarterly forecast and then use the selected technique for the next three quarters. For this system, a multiple forecasting model would be run on a yearly basis.

The dynamic vs. static analysis necessitates the need for a longer term evaluation and therefore attempts were made to replicate system performance over a specified time horizon. The previously used measures of performance, primarily the MIPE, are no longer appropriate since they do not lend, computationally and interpretively, to longer term evaluation. The Mean Absolute Deviation (MAD), which in reality is an average TAE measure, will now be used. For this study, the yearly MAD is defined as the average absolute error of four yearly forecasts made at quarterly intervals or updated quarterly. The quarterly MAD is the average absolute error of four quarterly forecasts. Tables 12 and 13 contain results for dynamic and static forecasting models.

TABLE 12
DYNAMIC SYSTEM PERFORMANCE
ITEM SAMPLE 3

COMMODITY	YEARLY MAD	%IMPROVEMENT OVER SAMMS	QUARTER MAD	%IMPROVEMENT OVER SAMMS
Construction	254	4	79	5
Electronics	116	18	43	12
General	167	14	59	9
Industrial	805	9	268	7
Medical	414	6	118	7
TOTALS	346	9	116	8

TABLE 13
STATIC SYSTEM PERFORMANCE
ITEM SAMPLE 3

COMMODITY	YEARLY MAD	%IMPROVEMENT OVER SAMMS	QUARTER MAD	%IMPROVEMENT OVER SAMMS
Construction	254	4	79	5
Electronics	119	16	43	12
General	170	12	61	6
Industrial	845	4	279	3
Medical	426	3	120	6
TOTALS	359	6	119	5

The dynamic system showed more improvement in all commodities except construction, where the overall results were identical. This analysis suggests that the dynamic system is more effective. It allows for some changes in the demand structure and the effect of selecting an inappropriate technique is not perpetuated for 4 quarters as in the static system.

One of the major concerns with the dynamic model is the potential for changing the forecasting techniques every quarter. This concern relates to the inherent assumptions within this type of multiple forecasting model. The assumptions are restated below.

1. One forecasting technique will be the best for a given item.

2. The technique that worked best in the past will work best in the future.

In other words, if a technique is the best this quarter, one would expect it to be the best the next quarter, and if its not the best next quarter, then maybe its not the best for that item. The later implies that the demand stream does not contain any definite time period from which the multiple forecasting model can select the best forecasting technique. Is this typical? Since the two assumptions are the basic principles upon which the forecasting model was constructed, an effort should be made to justify or validate their reasonableness and hence the integrity of the forecasting model itself.

The examination of this question focused on looking for occurrences of the same technique being selected frequently within some consecutive time frame. These occurrences could then be compared to a hypothetical case in which forecasting techniques are selected at random. This comparative analysis gives rise to two frequency distributions: observed vs. random or expected. The idea would be to conclude that the observed frequencies could not have come from completely random technique selections, and therefore, there exist some time periods from which techniques can be selected. More simply, the technique worked best in the past so it is likely to work best in the future.

Selected forecasting techniques for each item were gathered over a four quarter time horizon. The following definitions apply to this discussion and are referred to as levels of continuity. "All different" is used for those items for which each of four consecutively selected techniques is different. "One pair" is used for those items in which one pair of the four selections was the same technique. Similar definitions apply to "Two pair," "Three-of-a-kind," and "Four-of-a-kind." Overall, there are ten possible techniques, with replacement, (four single and the six 2-way combinations of the single techniques) from which the four techniques could be selected.

The observed frequencies for each level of continuity is now compared to random selections of four techniques. Employing the use of combinatorics one can obtain the expected number of times, under the random case, that each level of continuity would be observed.

TABLE 14
CONTINUITY OF TECHNIQUE SELECTION PROCESS
ITEM SAMPLE 3

	FREQUENCIES OBSERVED WITH MODEL'S SELECTIONS	FREQUENCIES EXPECTED FROM RANDOM SELECTIONS
All different	4126	20187.2
One pair	15160	17303.3
Two pair	4481	1081.5
Three-of-a-kind	10887	1441.9
Four-of-a-kind	5400	40.1
TOTALS	40054	40054.0

It should be noted that the expected values are based on the assumption that each technique is equally likely to be selected. Moreover, large sample sizes do not lend themselves to classical statistical analysis! For large samples, classical analysis typically leads to hypothesis rejection even though the distributions may be roughly similar (32 p20). For these two reasons, a classical goodness-of-fit test would be inappropriate. However, high frequencies are associated with the higher levels of continuity, such as three and four-of-a-kind, when compared to their expected values. Also, low frequency is observed for the lowest level of continuity. The forecasting model appears to be more likely to select the same forecasting technique that was previously chosen and thus some continuity exists from quarter to quarter.

Comparisons between the two distributions indicate that the selection process is not entirely random. This does not imply, necessarily, that a non-random process is better with respect to forecasting accuracy. Now, is continuity associated with increased forecasting accuracy? Indeed, as Table 15 illustrates, forecasting accuracy improves to a 19 percent error reduction as the level of continuity increases.

TABLE 15
TECHNIQUE SELECTION PERFORMANCE
BY CONTINUITY LEVEL
ITEM SAMPLE 3

	YEARLY MAD	%IMPROVEMENT OVER SAMMS	QUARTER MAD	%IMPROVEMENT OVER SAMMS
All different	413	4	136	2
One pair	397	7	130	5
Two pair	318	12	109	11
Three-of-a-kind	337	12	117	9
Four-of-a-kind	193	19	63	17
TOTALS	346	9	116	8

The last issue concerning a dynamic model is computer time. To get a better time estimate, the forecasting model was recoded to approximate its use in the production environment. This was accomplished by stripping out some of the features used for assessment that allowed various parameter changes to be made quickly. In essence the model was "hard-wired" but still in a modular form. The approximate computer time is 10 CPU minutes per 100,000 line items. So with Defense General Supply Center's Amdahl V8, the model can forecast roughly 100,000 items in about ten clock minutes.

3. Item by item. It was shown that average forecasting error decreased with multiple forecasting. One may ask if this lower error can be observed, significantly, on an item by item basis. The purpose of using the MIPE as a performance measure was an attempt to prevent the errors of a few items from dominating the results, and hence, the evaluation. The significance of the lower MADs produced by the forecasting model is next examined.

For this analysis, a nonparametric sign test was used. This test, or a variation of it, is typically used to compare the means of two distributions when the distributions are not well understood. Clearly, the model MADs, across all sample items, does not constitute a sample from a known distribution. Similarly, SAMMS MADs are not observations from a known distribution.

The testing procedure follows. First, count the number of items where a smaller error was observed as the result of the model's forecasts. Second, count the total number of model forecasts compared to SAMMS forecasts. Items with equal forecasting errors were excluded from these frequencies which are displayed in Table 16.

TABLE 16
FREQUENCIES OF IMPROVED FORECASTS
ITEM SAMPLE 3

COMMODITY	FREQUENCIES FOR LOWER OBSERVED MAD	PERCENT OF TOTAL	TOTAL NUMBER OF OBSERVATIONS
Construction	4698	.627	7495
Electronics	7013	.644	10887
General	3911	.652	5996
Industrial	6842	.674	10151
Medical	408	.608	671
TOTALS	22872	.650	35200

If forecasting error associated with the forecasting model and SAMMS are statistically indistinguishable, one would expect each to provide the best forecast 50 percent of the time. The sign test indicates that the probability of the observed frequencies occurring randomly is extremely small. Thus the errors produced by the forecasting model are smaller than those produced by SAMMS' forecasts. However, here again, care must be taken when using classical statistics or interpreting confidence levels derived from large samples. A more meaningful result is that an estimated 65 percent of the time forecasts produced by the multiple forecasting model will be more accurate than a SAMMS forecast. Due to the stochastic nature of demands, more accurate forecasts cannot be obtained for every forecast period for every item.

E. SYSTEM IMPACT. The Materiel Readiness System's Performance Projection Model (PERMES) was used to evaluate the forecasting model's impact on supply availability and stock fund investment. PERMES, by using inventory control theory and historical demand variance, computes future supply performance and expected requirements (26). The MAD provides the historical demand variance estimate for DLA's inventory system.

MADs for the model and SAMMS were computed from four quarterly forecasts for the population of items evaluated in this study. Both sets of computed MADs and new forecasts were then overlaid onto the PERMES data files. Computed MADs, used as PERMES input for the population of items in this study, are displayed in Table 17. This table also provides the percent improvement over SAMMS for these items and thus the best estimate for quarterly MAD reduction associated with the forecasting model.

TABLE 17
PERMES INPUT: MEAN ABSOLUTE DEVIATION
POPULATION

COMMODITY	NUMBER OF ITEMS	QUARTERLY MAD AVERAGE SAMMS	QUARTERLY MAD AVERAGE MODEL	%IMPROVEMENT OVER SAMMS
Construction	80668	83	79	4
Electronics	130184	35	32	9
General	75664	58	52	10
Industrial	215370	298	270	9
Medical	9771	97	93	4
Total	511657	158	144	9

Preliminary PERMES runs were made to determine the system constants and the number of requisitions. The system constant is the sum for each commodity of the product of each item's unit price and lead time MAD. Hence it is a fixed quantity determined by forecasting accuracy.

The number of requisitions was used to estimate the Beta goals for established backorder lines. The Beta or established lines backordered goal is indirectly used by SAMMS as a supply availability goal and SAMMS computes the associated safety levels required to achieve this goal. Attempts were made to obtain current goals that are established by supply center. However these values apply to all items managed by each respective center, not just those included in this study. The PERMES preliminary analysis data is shown in Table 18.

TABLE 18
PRELIMINARY PERMES STATISTICS
POPULATION

COMMODITY	ANNUAL REQUISITIONS	CURRENT SAFETY LEVEL($T)	SYSTEM CONSTANT COMPUTED MODEL	SYSTEM CONSTANT COMPUTED SAMMS
Construction	2995972	168825	173267792	186084432
Electronics	1853896	51074	94713552	102558000
General	806847	107470	119592992	129715088
Industrial	4475067	129698	182405952	198693840
Medical	309906	21250	15710362	16861232
Total		478317		

Beta goals and the system constants provide the needed input for complete analysis runs. System constants for each scenario, forecasting model and SAMMS, were taken directly from Table 18. However, to get a better understanding of the importance of the Beta goals in supply performance and safety levels, the sensitivity of safety level dollars to Beta changes was analyzed. PERMES analysis runs were made for Beta goals of 6, 3, 1.5, and 1 percent of the number of annual requisitions. A Beta goal of 6 percent would imply an annual fill rate of 94 percent. This fill rate appears unreasonably high, but PERMES is a projection model which may over estimate availability due to its method of stochastical demand generation. More importantly, however, is that current safety levels, which are depicted in Table 18, are more accurately reflected in the higher Beta goals.

The same Beta values that were used to approximate the safety levels associated with the model's forecasts were also used for the levels associated with SAMMS' forecasts. The implication of this analysis is that one would expect PERMES to compute approximately the same projected supply availabilities for both scenarios. However a slight improvement in supply availability was observed with model MADs and forecasts. Graphs depicting the impact on supply availability and safety level of the various Beta goals are contained in Appendix B. Table 19 represents the estimated safety level reduction, in thousands, based on a Beta goal that most closely reflects the current safety levels.

TABLE 19
PERMES SAFETY LEVEL ANALYSIS
POPULATION

COMMODITY	BETA GOAL AS % ANNUAL REQUISITIONS	SAFETY LEVEL COMPUTED ($T) MODEL	SAMMS	SAFETY LEVEL REDUCED ($T)
Construction	1.0	105232	115916	10684
Electronics	1.5	50160	57328	7168
General	1.0	84524	94673	10149
Industrial	1.0	107050	120273	13223
Medical	1.0	8774	9463	689
Estimated Savings				41913

The estimated one-time savings in safety level reduction is $42 million. Results indicate that this reduction can be accomplished at no sacrifice to supply availability.

The estimated savings compares favorably with the assumption that for each 1 percent reduction in MAD there is a corresponding 1 percent reduction in safety level. Employing this method, the overall 9 percent MAD reduction given by the forecasting model (see Table 17) times the total current safety level of $478,317,000 (see Table 18) for these items yields an estimated savings of $43 million. This is indeed a comforting result although somewhat surprising. The method for estimating savings, described here, was successfully used for a previous DLA demand forecasting study (20).

F. MONTHLY FORECASTING. An issue of concern by the Requirements Forecasts Working Group for implementation is with the frequency of forecasting. Monthly forecasting is taken to be a forecast generated from monthly demands. The medical commodity was selected for this analysis for the following reasons. First in comparison across commodities, medical items typically showed less improvement over SAMMS' forecasts (see Table 17). Second, there appears to be more items with rapidly changing demands which suggests that items are phased in and out of use more rapidly. Finally this commodity is associated with shorter procurement cycles (see Table 1) which would imply more frequent buying decisions. Together these observations suggest a greater urgency for monthly forecasts.

Two scenarios were evaluated. First, sixteen quarterly demand observations were multiple forecasting model inputs. The forecasting model estimated the future annual requirements by multiplying the quarterly forecast by four. Secondly, sixteen monthly demands were used as inputs and future annual requirements were obtained by multiplying the monthly forecast by twelve. The premise of this analysis was that the monthly forecast would be more responsive to the most **recent changes** in the demand stream.

Again because of the unknown underlying distributions, a nonparametric sign test was used. First, count the number of items where a lower annual error was observed as the result of model forecasts based on quarterly demands. Second, count the total number of observations when model forecasts based on quarterly demands compared to model forecasts based on monthly demands. Items that had equal forecasting errors were excluded from the frequencies displayed in Table 20.

TABLE 20
FREQUENCY OF IMPROVED FORECASTS WITH QUARTERLY DEMANDS
SAMPLE 3

COMMODITY	NUMBER OF TIMES A LOWER ERROR WAS OBSERVED	PERCENT OF TOTAL	TOTAL NUMBER OF OBSERVATIONS
Medical	427	.593	720

The nonparametric test would indicate that the probability of the observed frequencies occurring randomly is very small. In other words, a probability greater than 50 percent exists for obtaining more accurate forecasts with quarterly demands. Due to the large sample size and the use of classical statistical procedures, this does not imply a great deal of information. A more meaningful conclusion is that annual forecasts with greater accuracy were obtained approximately 60 percent of the time when the forecast for annual requirements were based on quarterly demands. This should be viewed as the approximate probability of obtaining a more accurate forecast. A 7 percent improvement in absolute annual forecasting error was also observed. Most likely this result is explained by greater monthly demand instability which creates more instability in long-term forecasts. Similar conclusions were drawn under a previous DIA study (20).

G. FOLLOW-ON ANALYSIS. In this follow-on analysis two questions were addressed with respect to the multiple forecasting model's performance. This analysis is critical due to certain weaknesses within the forecasting model. In particular, apparently erratic demands cannot be explained, and must therefore, be dampened to downplay their impact for forecasting future requirements. From a statistical sense this approach is somewhat naive in that inherent bias may be incorporated within the demand forecast or the demand variance estimator, the MAD. Are the forecasts biased? Is the reduced MAD, which is a by-product of the model's forecast, an appropriate estimator for demand variance?

1. Bias. If the forecasting model produces biased forecasts then these forecasts would consistently under, or consistently over, estimate future demands. The number of times the model under and over forecasts annual demand is compared to the number of times SAMMS under and over forecasts annual demand. Items with the minimum forecast of one and zero demand were not included in the following table.

TABLE 21
FORECASTING BIAS
SAMPLE 3

GENERAL COMMODITY	NUMBER UNDER	NUMBER OVER	PERCENT UNDER	PERCENT OVER
MODEL	3256	4056	44.5	55.5
SAMMS	2933	4390	40.1	59.9

A tendency exists for over-forecasting item demand. This tendency is slightly diminished for the model's forecasts. One explanation is that low demand items tend to limit the potential for obtaining a smaller forecast regardless of the forecasting methodology employed.

2. Standard Deviation Estimator. The MAD plays an important role in DLA's inventory system as a demand standard deviation estimator. Based on theoretical work contingent upon an exponential forecast (14 p37-41, 25 p282-287, 28, 29 p14-20), the error measure is shown by simulated data to be appropriate for some demand distributions, such as the normal distribution. The general approximation follows.

$$\sigma = \beta * \text{MAD}$$

where: σ = standard deviation of demand
β = scaling factor

The scaling factor is considered to be 1.25 for normally distributed demands and is the value used by DLA. Here, the MAD is a single exponential smoothed value.

Under the normally distributed demand assumption and using the forecast as the expected value of demand the following is derived:

Let $X_1, \ldots, X_n$ be n independent observations, or item demand quantities for n items, each from a normal distribution with μ_i = expected value of X_i, σ_i = standard deviation of X_i, and i=1, ..., n. Then

$$Pr(| X_i - \mu_i | < a\sigma_i) = p_a$$

where: a = a scaler such as 1,2,3, or 4
p_a = a constant that is independent of the item's demand distribution's parameters

Based on this result one can compute the expected number of observations for various values of "a". Observed frequencies were tabulated by using 1.25*MAD as the demand standard deviation estimate, X_i represents the actual demand for item i, and μ_i is the forecast or expected value of demand for that item.

More simply, this implies counting the number of items which experienced demand less than three standard deviations below the forecast, between two and three standard deviations below the forecast, between one and two standard deviations below, and so on. Each freqency category is contained in Table 22. Negative "a" values indicate demands below the forecast while positive values indicate those above.

TABLE 22
DEMAND DISTRIBUTION
MAD AS STANDARD DEVIATION ESTIMATOR
GENERAL COMMODITY

VALUE OF "a" MIN	MAX	MODEL MAD NUMBER OBSERVED	SAMMS MAD NUMBER OBSERVED	NUMBER EXPECTED
$-\infty$	-3	6	2	9.7
-3	-2	23	28	161.1
-2	-1	338	519	1018.4
-1	1	6096	5971	5115.4
1	2	486	453	1018.4
2	3	197	209	161.1
3	∞	348	312	9.7
		7494	7494	7493.8

There are a few features that deserve to be mentioned when comparing the observed and expected frequency distributions. It appears that for a larger number of times, demands are observed that are within one standard deviation of the forecast, or mean. Second the lower half of the distribution is observed with smaller frequencies than the upper half. Finally the general shape of the observed and expected distributions is similar. Although this test does not indicate when the MAD is a good estimate for the standard deviation, some conclusions can be drawn.

If the two observed distributions are really different from the expected distribution then the potential exists for two problems to emerge. First, the MAD may not be an appropriate demand variance estimator. Second, the normality assumption does not hold.

Since the observed and expected distributions are somewhat different, especially in the tails, the MAD resulting from the multiple forecasting model, may not be a valid estimator. Similarly, this result can be applied to the MAD that is a by-product of SAMMS' forecasts. Therefore, most of the problems associated with the MAD must be in the assumption of normally distributed demands. The normal assumption cannot be unconditionally used for all demand replenishment items. Items with small demand frequencies and quantities are most likely contributing to this problem.

X. CONCLUSIONS

A multiple forecasting model that optimally selects a forecasting technique, such as the one presented here, works for DLA items. When long-term forecasting accuracy is desired, the best technique, of all unbiased techniques, should have the smallest MSE computed from four one-step ahead forecasts. This criteria minimizes the potential for larger forecasting errors and becomes critical when the large forecasting error is multiplied to obtain lead time demand.

The method for demand dampening applied in this study greatly improved the model's forecasting performance. This procedure not only improves the accuracy of the selected technique, but also increases the likelihood of selecting a more appropriate technique.

Use of nonrecurring demands gave more conflicting results. There is some indication that applying smaller percentages of nonrecurring demand to the forecast can improve accuracy. However this demand classification is most likely not applied evenly and its removal from forecast generation may inherently bias the forecasts.

Forecasting techniques to be included in a multiple forecasting model should minimize the potential for an extreme forecast. Moving averages, single exponential smoothing, and regression techniques are appropriate. Some technique diversity exists; however, the capacity for over-reacting to one-time or rare demand spikes is minimal.

For the QFD items studied, forecasting error can be reduced by 9 percent with a multiple forecasting model. Increased forecasting accuracy has an impact on safety levels. Without decreasing supply availability, the potential one-time safety level reduction is $42 million.

Implementation of a multiple forecasting system should center on a model that is run dynamically. Each quarter a new technique assignment is made. Associated with a dynamic system are smaller forecasting errors and high probabilities of forecasting with a technique selected in a previous quarter.

In addition the forecasts should be based on quarterly demands. Quarterly demand observations provide more stable long-term forecasts and increase the likelihood for an improved forecast. Appendix C contains the data requirements of a multiple forecasting model.

Follow-on analysis reveals some indication of possible shortcomings associated with the MAD under a multiple forecasting system.

XI. RECOMMENDATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

Specific recommendations stemming from this project are the following:

▸ A multiple forecasting model, as defined by the criteria developed in this study, should be implemented to provide demand forecasts for DLA items. This recommendation applies only to those QFD items with sufficient demand histories since these items constituted our test base.

▸ Items with shorter demand histories, less then 16 quarters, can use the SAMMS' forecasting method which would have the additional benefit of establishing the MAD quantity.

▸ The implementation should be conducted in stages with appropriate evaluation preceeding each stage.

▸▸ Develop working prototype at a hardware center. DORO will be available for technical assistance and support.

▸▸ Concurrent and subsequent to the prototyping efforts the following areas should be addressed by the RFWG:

▸▸▸ DLA demand forecasts are and will be inaccurate, as suggested by MADs greater than QFDs. How do we best cope with inaccurate forecasts? How do we identify which items can be managed more effectively as non-demand based, and hence, not forecasted?

▸▸▸ This study has focused on a multiple technique approach to forecasting item demands. However the techniques presented in this study are similar in that they are all time-series methods. Can demand projections be based on non-time series models as well, for example relating production rates and back-orders? If so, what extrinsic factors are readily available for use?

▸▸▸ Can less restrictive forecasting methods that are not bounded by conventional weighting schemes be used more effectively? One such method has been proposed by DESC which incorporates pattern recognition techniques through neural networks. Although this type of application would require additional research, it is our opinion that this method could be included as a forecasting technique within a multiple forecasting model.

▸▸▸ There is some indication of possible problems associated with the MAD under a multiple forecasting system. Do better methods exist for estimating this essential data element used in SAMMS requirements computations?

▸▸ The effectiveness of the prototype, with respect to forecasting accuaracy and system impact, should be evaluated by the RFWG prior to full implementation.

APPENDIX A

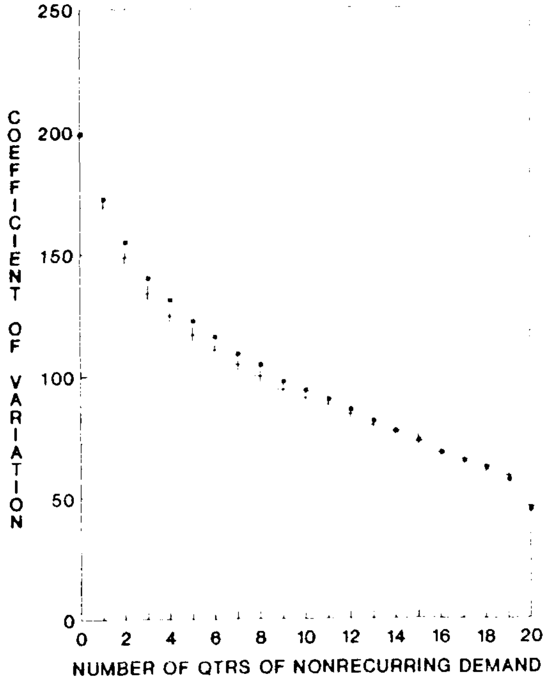
This Appendix supports discussion on recurring and nonrecurring demand base analysis, Section IX.C.2, page 21.

NONRECURRING DEMAND ANALYSIS

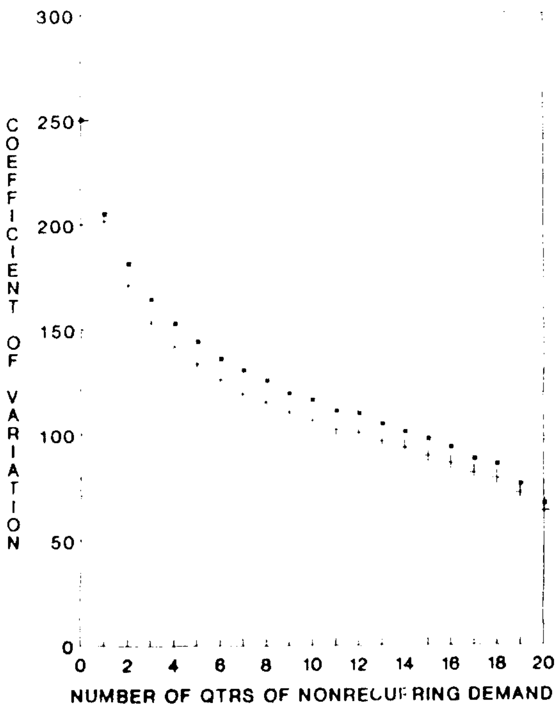
• RECURRING DEMAND

+ TOTAL DEMAND

DCSC



DESC



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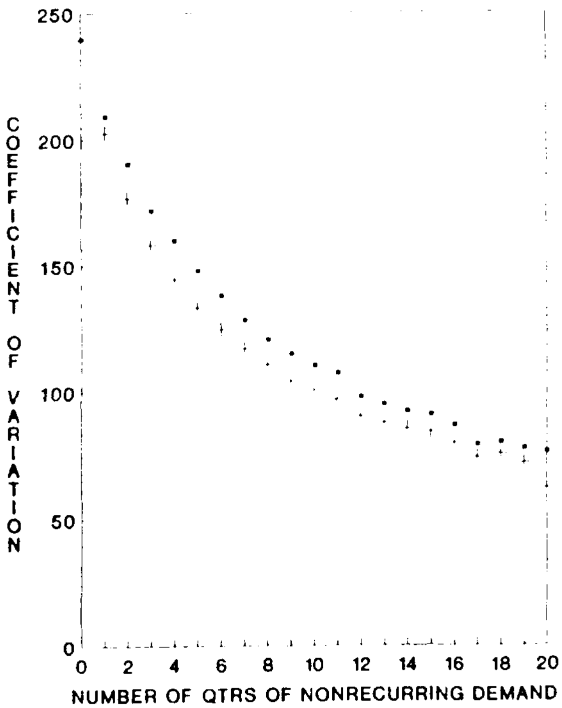
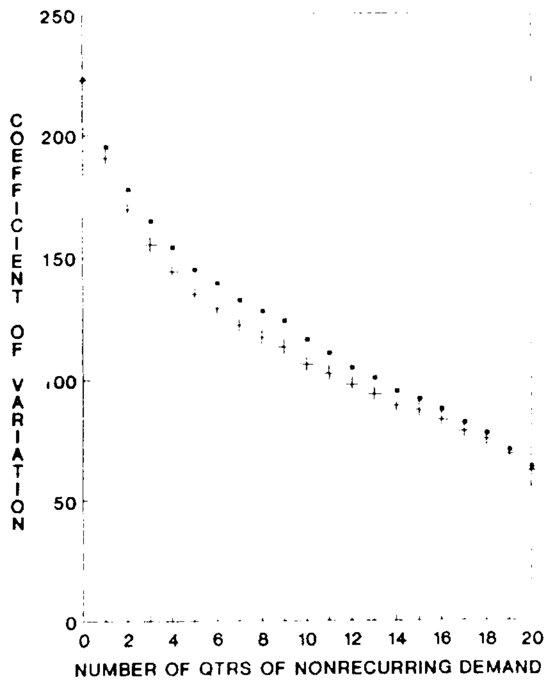


NONRECURRING DEMAND ANALYSIS

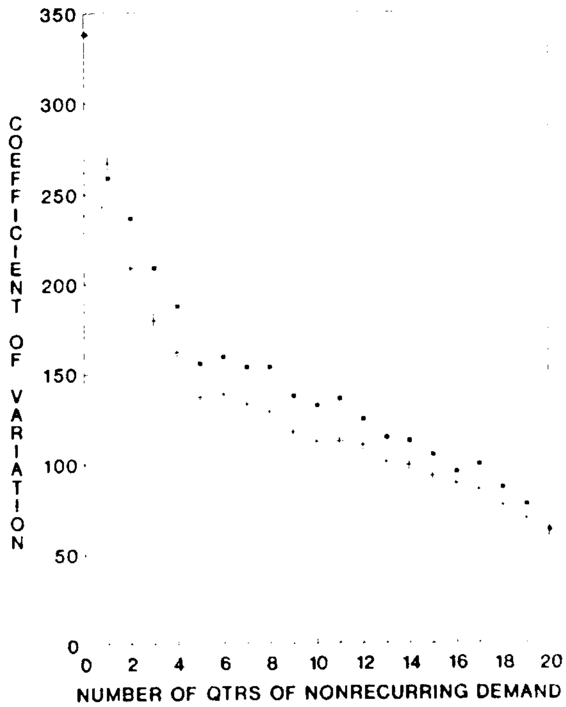
• RECURRING DEMAND

+ TOTAL DEMAND

DISC



MEDICAL



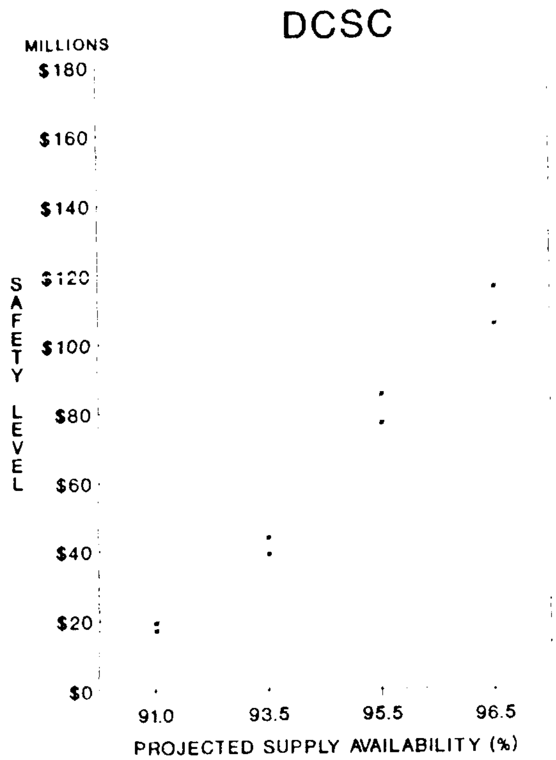
APPENDIX B

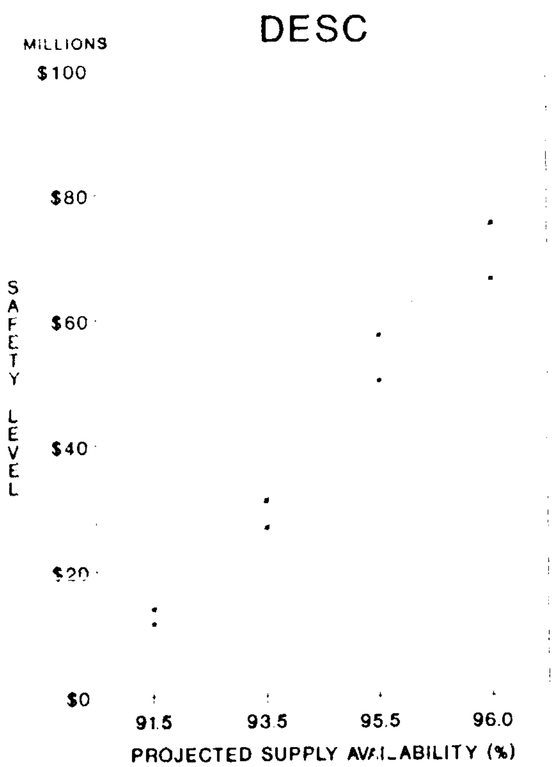
This Appendix supports discussion on PERMES safety level analysis for the system impact, Section IX.E, page 31.

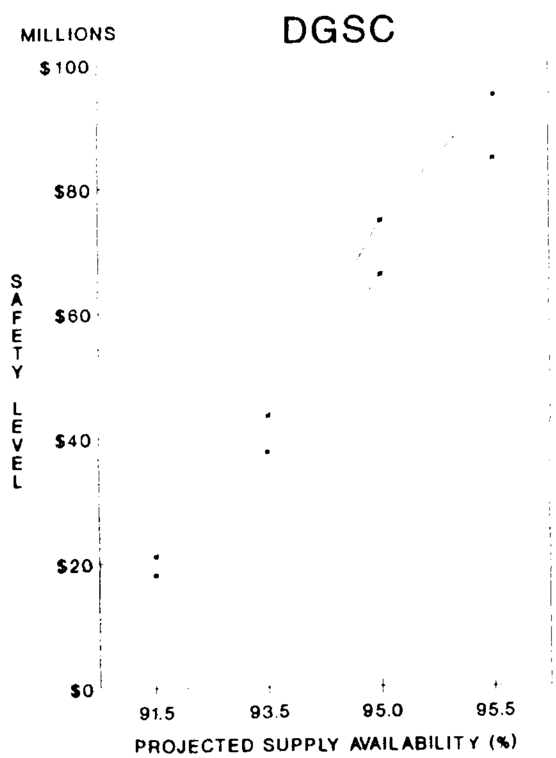
SAFETY LEVEL REDUCTION

--- MODEL

—— SAMMS



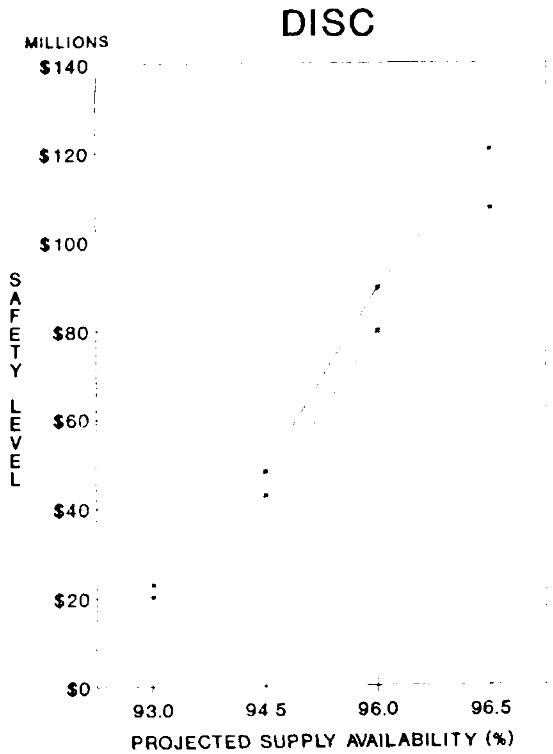


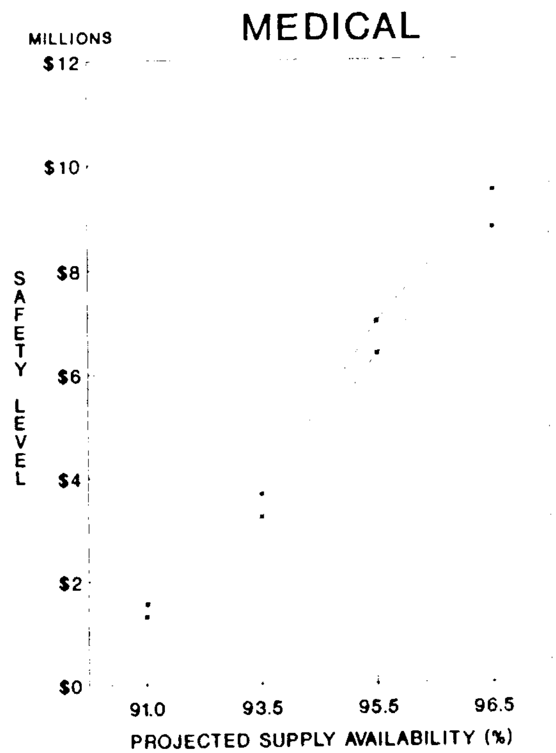


SAFETY LEVEL REDUCTION

- - - MODEL

——— SAMMS





Appendix C

PROJECTED DATA REQUIREMENTS FOR MULTIPLE FORECASTING SYSTEM

Projected system input requirements are the following:

FIELDNAME	BYTES
Defense Supply Center (DSC)	1
National Stock Number (NSN)	13
Item Category Code (ICC)	1
Supply Status Code (SSC)	1
Age of Item Code (AIC)	1
Forecast Basis Code (FBC)	1
Administrative Lead Time (ALT)	3
Production Lead Time (PLT)	3
Procurement Cycle Months (PCM)	3
RECURRING DEMAND: Past 16 Quarters	9 each
NONRECURRING DEMAND: Past 16 Quarters	9 each

In addition the system would likely maintain the following histories:

Selected Forecast Technique Code: Past 16 Quarters	1 each
Actual Forecast History: Past 16 Quarters	9 each

Additional inputs and histories may be required.

Appendix D

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Currently the Standard Automated Materiel Management System (SAMMS) uses a single technique to forecast demand for all hardware items. SAMMS forecasts are being adjusted by supply center with locally developed forecasting programs and manual inventory manager intervention. Previous DLA studies have focused on finding a single technique to improve forecasting for all items. A demand forecasting study of subsistence items has found that a set of four simple methods could perform better than the current subsistence techniques. The purpose of this study was to define the criteria for a multiple forecasting model to operate in conjunction with the current SAMMS system and data base. The multiple forecasting model optimally selects the most appropriate forecasting technique for each item.

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